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Prediction of GMA welding characteristic parameter by artificial neural network system

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Abstract

Nowadays, demand for automated Gas metal arc welding (GMAW) is growing and consequently need for intelligent systems is increased to ensure the accuracy of the procedure. To date, welding pool geometry has been the most used factor in quality assessment of intelligent welding systems. But, it has recently been found that Mahalanobis Distance (MD) not only can be used for this purpose but also is more efficient. In the present paper, Artificial Neural Networks (ANN) has been used for prediction of MD parameter. However, advantages and disadvantages of other methods have been discussed. The Levenberg–Marquardt algorithm was found to be the most effective algorithm for GMAW process. It is known that the number of neurons plays an important role in optimal network design. In this work, using trial and error method, it has been found that 30 is the optimal number of neurons. The model has been investigated with different number of layers in Multilayer Perceptron (MLP) architecture and has been shown that for the aim of this work the optimal result is obtained when using MLP with one layer. Robustness of the system has been evaluated by adding noise into the input data and studying the effect of the noise in prediction capability of the network. The experiments for this study were conducted in an automated GMAW setup that was integrated with data acquisition system and prepared in a laboratory for welding of steel plate with 12 mm in thickness. The accuracy of the network was evaluated by Root Mean Squared (RMS) error between the measured and the estimated values. The low error value (about 0.008) reflects the good accuracy of the model. Also the comparison of the predicted results by ANN and the test data set showed very good agreement that reveals the predictive power of the model. Therefore, the ANN model offered in here for GMA welding process can be used effectively for prediction goals.

1. Introduction

Gas Metal Arc Welding (GMAW) is an attractive welding method due to its high speed and feasibility of both manual and automatic welding modes for wide range of ferrous and non-ferrous metal parts [1]. It is more than two decades that GMAW is widely used in pipeline technology [2]. During this time it has been consistently tried to improve the speed and quality of the process. Using automatic GMAW is the most recommended solution in this way [3]. So that, many investigations have been dedicated to study automatic welding systems [4]. Artificial neural network (ANN) is an important method in quality control of the welding system and to date, numerous studies have been developed to evaluate the welding parameters using ANN systems.

Generally, welding quality is affected by two sets of parameters including welding design and welding process parameters [5]. Repair costs and even non-destructive evaluation costs can be reduced considerably by obtaining acceptable welding quality through good choice of these parameter sets. For a long time GMAW has been used in pipeline industry and the optimal values of process parameters have been obtained and reported in literature [3]. Now, the main challenge is to ensure the stability of welding parameters and eliminate the undesired changes during welding. One important parameter in GMAW is the Heat transfer [6]. Because of high impact of heat transfer on weld geometry and molten pool thermal properties, automatic control of the variables is very important. Heat transfer is affected by GMAW variables such as arc current, arc voltage, heat input, melting rate, and gas composition [7]. Typically, heat transfer is controlled by the current and voltage. It has been reported that if the combination value of input current and arc voltage exceeds from a specific statistical value named Mahalanobis Distance, MD, then a poor welding quality is expected [8].So, acceptable combination of voltage and current values for use in welding process can be obtained by introducing MD factor. Input current and arc voltage have been chosen because they greatly affect the welding quality and in the mean time they are considered to be the feedback parameters of the system. It means that their values can be changed during the process when it is needed to improve the welding quality.

In parallel with developments on welding quality parameters, prediction methods such as Genetic Algorithm, Artificial Neural Network, Response Surface Methodology, Taguchi and etc have been developed to predict and control of physical processes including welding. However, each of them can be efficiently used in a specific range of applications depending on the nature of the process. Artificial Neural Network (ANN) was found to be the most accurate system in prediction of characteristic parameters in GMAW process and then ANN system is used in this study. Weld bead width and height were the most interested welding quality factor in previous researches. For example Kim et al. [9] used neural network and multiple regression methods to understand relationships between process parameters and top-bead width in robotic GMAW process. The main goals of the current work are to evaluate the MD factor as a characteristic parameter of the GMAW process and to find the optimal MLP architecture for this process. Hence different number of layers and neurons in each layer of ANN system are studied.

2. Selection of the most suitable prediction method

Arc welding is used to join two or more materials, through fusion, such that the joint exhibits a sufficient strength and fracture toughness. Generally, the heat required for melting and subsequent fusion of material is generated by an electric arc bridged between work piece and the welding electrode in an inert atmosphere that helps to prevent oxidation. The current passing through this arc is in the range of 180A to 600A depending on the material thickness, electrode diameter and shielding gas mixture. Essentially, combination of arc stability and regulation of the rate and mode of 'metal transfer' dictates the weld quality. These properties are the integration of many interdependent aspects of the process, thus making GMA welding a fully coupled, highly non-linear multivariable process [10] . Actually, there are several prediction methods that can be used for controlling GMA welding process. Hence, the best of these methods should be chosen. Correia et al [11] compared the Genetic Algorithms (GA) and Response Surface Methodology in optimization of GMA welding to find which method is better in determination of the optimal GMAW process parameters including welding voltage, wire feed speed and welding speed. They reported that the GA can be a suitable tool in experimental welding optimization. There was maximum difference of 4% in the most important response (depth of penetration) between the predicted value by GA and its target. However, optimization by GA technique requires a good setting of its own parameters, such as population size and number of generations. Otherwise, there is a risk of an insufficient sweeping of the search space.

Response surface methodology (RSM) is a method used in GMAW control system. RSM provides good results over regular experimental regions, i.e., with no irregular points. However, it is often very difficult to establish an arc and melt-through may occur under certain experimental points needed to satisfy the specific experimental design. It may become impossible to analyze the obtained data or it may provide poor results in such cases. Furthermore, a good comparison between neural network and multiple regression methods is offered by Kim et al. [12]. They finally conclude that ANN system is preferred in prediction aim of robotic GMAW process.

Acoustic method is another developed technique for prediction of the system quality. Acoustic characteristics of welding zone are also a clue of welding quality that was attracted researchers. Tam [10] used this characteristic to predict the feedback parameters such as arc voltage, based on emitted acoustics from welding zone. Similar work is reported by Horvat et al [13]. Joseph Tam firstly gathered data by changing input parameters and measuring related acoustics. Then, he fed the data into ANN system for learning and modeling and found the relationship between input parameters from acoustic characteristics such as frequency and intensity. In this method, the input parameters could be predicted by measuring the acoustic characteristics. Application of this method is relatively difficult and the discrepancy between the predicted and the measured values is relatively high (about 4.5%).

Yarlagadda [14] used the design of experiment method for optimizing weld bead geometry in GMAW process. He employed simulated annealing algorithm to minimize the error function consisting the desired and calculated weld bead geometry. The error value was almost 0.02 which is higher than the error values in the proposed ANN system of the current paper for prediction of weld quality characteristics.

Artificial neural network (ANN) has relative advantages in terms of computation time, model developing, understanding and its application. Additionally, neural systems are more suitable for dynamic and on-line systems. ANN has efficiently been employed in quality control of the welding system. Kim et al [15] used this method in prediction of the weld bead width. They used a multi-layer back-propagation network for mapping process parameters such as pass number, welding speed, welding current and arc voltage into the bead width to predict the optimal bead width in robotic GMA welding process.

One distinguished difference of current study with previous ones is application of MD as a characteristic parameter incorporated with ANN system. Using MD as a quality factor in ANN system is advantageous because it can be easily predicted and can be precisely used in decision making. Although there are many predictive methods that are used in GMAW process, the ANN system with the configuration used in the current study is the most powerful, precise and adaptive technique in prediction of GMA welding quality.

3. Materials and Method

Artificial neuron model was proposed by McCulloch and Pitts in 1943. When two or more artificial neurons are combined they get an artificial neural network (ANN).The method is vastly used in engineering problems for various objectives. Yarlagadda [14] used this method in prediction of process parameters in metal injection moulding. In another work Yarlagadda et al [16] used ANN system in order to predict bead height in robotic GMAW process. ANN's architecture plays an important role in achieving precise result for the aim of modeling [14]. Neural network architecture defines the structure including number of hidden layers, number of hidden nodes and number of output nodes of ANN system [17]. Hidden layer(s) provide the network with its ability to generalize. In theory, a neural network with one hidden layer with a sufficient number of hidden neurons is capable to approximate any continuous function. However, there is no magic formula to obtain the optimum number of hidden neurons. The optimal number of neurons in this study is achieved by trial and error. Since there is a little pre-modeling knowledge about the relationship between input parameters and target in GMAW process, a multilayer feed forward neural network or multi layer perceptron (MLP) is the most suitable type for this study.

The base material used in GMA welding of this study was BV-AH32 steel with 12mm thickness. The GMA welding system and an automatic travelling unit were combined to make an automatic process. Experimental test sheets were located in the fixture and the required weld conditions were fed for the particular weld steps in the robot path. With power supply and argon shield gas turned on, the robot initiated the movement and the welding was executed. The experimental setup used in this study is presented in Fig. 1.

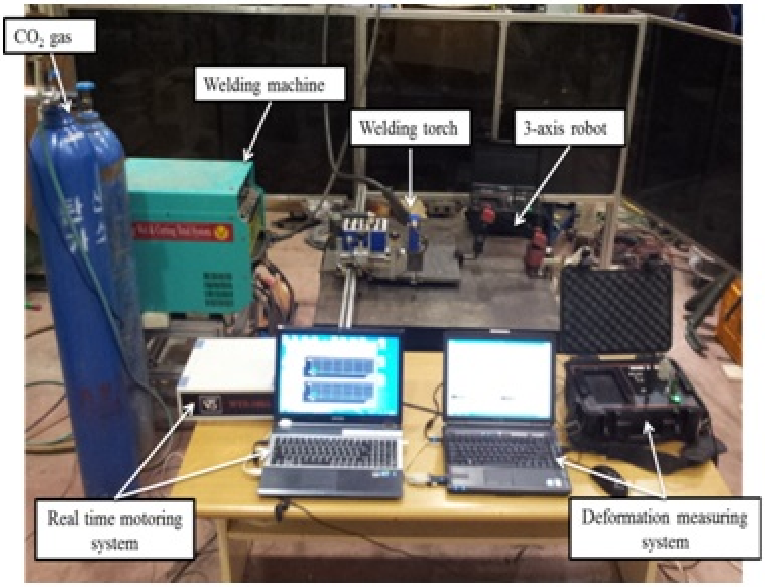

Fig. 1: The experimental setup of this study

It was aimed to distinguish the faulty weld from accepted one by recording the changes in current and voltage. But how much changes are clue for faulty weld is a matter that can be studied by definition of statistical feature of Mahalanobis Distance (MD). The welding quality whether it is faulty or good can be determined by the observation over MD space of the multivariate outliers. For quantifying the welding quality during welding process, the data, consisting the transformed current and voltage with rate of 2500 data per seconds were obtained and changed from analog to digital. Then the MD values as a characteristic feature of the welding process were extracted and were fed into artificial network to find the relationship between input parameters and MD factor. The schematic of the working procedure is shown in Fig. 2.

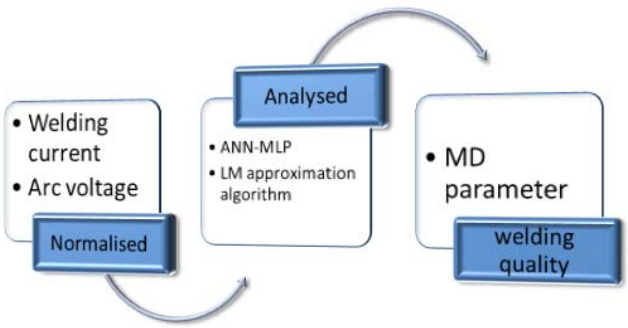

Fig. 2: Modeling procedure of the GMA welding process.

4. Input Parameters Selection

The first step in developing a predictive model is to choose the input parameters. Selection of input parameters is a fundamental, and yet crucial consideration in identifying the optimal functional form of GMA welding process. Selection of the input variables is difficult because of (i) the number of available variables, which may be very large; (ii) correlations between potential input variables, which create redundancy; and (iii) variables that have little or no predictive power. Significance of input parameters selection for general problems and the related criteria have been elaborated in former studies[18].

ANN model is sensitive to input parameters, i.e. may be specified with insufficient input variables, or more inputs than what is strictly necessary. If greater number of input variables is fed, then the size of an ANN increases and the computational burden associated with querying the network increases—a significant factor in determining the training speed. In design of predictive model for automated welding process the quick analyzing with quick feedback response is crucial. If all welding parameters such as input current, arc voltage, temperature and cooling rate, weld pool geometry, droplet transfer frequency, welding speed, filling diameter, and mass transfer are considered the input layer of MLP will have an increased number of incoming connection weights. Then not only the ANN size will increase, but also an increased burden on data pre-processing steps such as data normalization during ANN development will be placed. It is known that as the dimensionality of a model increases linearly, the total volume of the modeling problem domain increases exponentially. Hence, an exponentially increasing number of samples are required to map a given function over the GMA welding process with sufficient confidence. Furthermore, the effect of redundant variables is to increase the number of local optimal in the error function that is projected over the parameter space of the model, since there are more combinations of parameters that can yield locally optimal error values. These are where, in practice normally all parameters in automatic GMAW process are sets on their pre-specified optimal values and the main need for an artificial neural network raise from this fact that there is no spontaneous consistency during the welding process and ANN system can bring this for a process. Among all parameters, input current and arc voltage play key role in control of the consistency of welding process and in the mean time are practically controllable during welding process. Actually, if other parameters are fixed on their practical optimal values; these parameters are fairly enough for having control on welding quality. Therefore, in this study these parameters are chosen as input parameters in ANN system.

5. ANNs for GMA welding

It has been reported that multilayer ANN models, with only one hidden layer are universal approximators [17]. Hence, a three-layer feed forward neural network (Fig. 3) is chosen as a regression model. As the magnitudes of inputs and outputs greatly differ from each other, they are normalized in 0–1 scales using the following relation:

$$x_{normalised}(i) = \frac{\frac{X(i) - \frac{Max(x(i)) + Min(x(i))}{2}}{X_{max} - X_{min}}}{\frac{Max(x(i)) + Min(x(i))}{2}}$$

In this relation X, stands for a given parameter e.g. input current and arc voltage. $X\,(i)$ denotes the value of X in i^{th} experiment. The input set was including about 12500 experimental data obtained from the experiment. It is found that the start and end parts of data, relating to the separation of torch from weld piece, defines instable relationships and then are omitted from data set. Therefore, only 11000 numbers of data were used in this study. 90%of total data set was chosen randomly for training and rest 10% was kept for validation.

Number of the neurons in the hidden layer is up to the discretion of the network designer and generally depends on the complexity of the problem. With too few neurons, the network may not be powerful enough for a given learning task. With too much number of neurons (and connections), computation becomes very expensive and time consuming. In the present study, the optimum number of neurons is calculated by trial-and-error method which is 30 in the hidden layer of the current problem. The sigmoid function was selected in the hidden and output layers. Neural learning is considered successful only if the system can perform well on test data on which the system has not been trained. This capability of a network is called generalizability. Algorithms such as back-propagation algorithm, which are based on gradient descent, are therefore more likely to converge to a local optimum, resulting in poor generalization performance. Also the training of the network in back-propagation algorithm is slower.

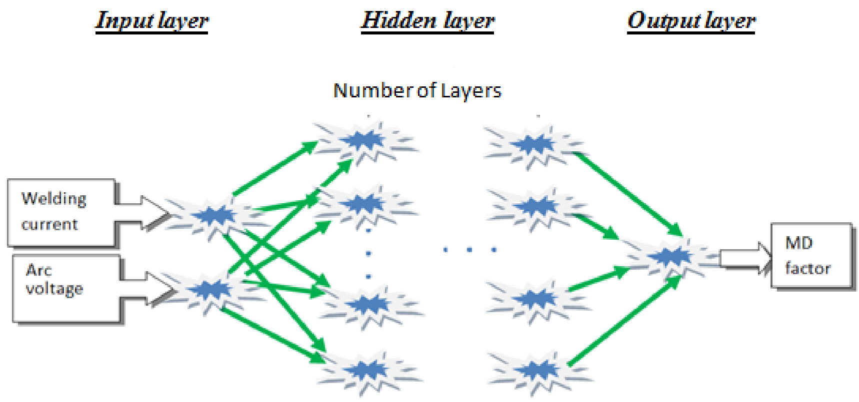

Fig. 3: Neural network architecture for predicting MD factor

In a work, Yarlagadda [14] compared three different training algorithms namely: error back-propagation algorithm; momentum and adaptive learning algorithm; and Levenberg–Marquardt approximation algorithm. He found that the Levenberg–Marquardt approximation algorithm is the preferred method as it reduces the sum-squared error to small values. However, Levenberg–Marquardt algorithm requires computation of the Jacobian *J* matrix at each iteration step and the inversion of J^TJ square matrix. In total, in Levenberg–Marquardt algorithm an N by N matrix must be inverted in every iteration, and the computational time is high. So, it is not recommended for large size neural networks with large number of parameters. But for the current study it converges relatively fast with a very acceptable accuracy. Therefore, it is employed for network training in this work.

6. Results and Discussion

In automatic GMA welding, for having control over welding quality, it is very important to know which relation is valid between input parameters and the welding quality factor. The relationship between input parameters and the quality factor is complex and non-linear. ANN systems are very powerful in modeling non-linear relationship between input and output parameters. Practically in automatic GMA welding, arc voltage and input current define the feedback mechanism for the system. But firstly it should be assured that these inputs have enough correlation with MD factor. For this it used the correlation coefficient matrix that represents the normalized measure of the strength of linear relationship between parameters. The correlation coefficient between two variables, X and Y, with standard deviations σ_X and σ_Y is their covariance normalized by their standard deviations, as follows:

$$Correlation\ Coefficient = \frac{cov(X,Y)}{\sigma_x \sigma_Y}$$

The correlation coefficient matrix is used to insure about the significance relationship between input parameters and MD factor in GMAW process. Then this matrix is established for online recorded data from experiment. The results are as following:

$$Correlation\ Coefficient\ Matrix = \begin{bmatrix} 1 & -0.695 & 0.643 \\ -0.695 & 1 & -0.513 \\ 0.643 & -0.513 & 1 \end{bmatrix}$$

In this matrix the diagonal elements indicate the auto-correlation for target parameter means MD which is equal to one that is very natural and the cross-correlation of voltage with current is about 0.513. It is desired this type of correlation between input parameters to be low, but from where voltage and current have a known inter-relationship, this amount of correlation coefficient is expected. The cross-correlation between voltage and current with MD are respectively, -0.695 and 0.643. The higher values for correlation between input and output parameters are desired.

The accuracy of the network was evaluated by the root mean squared (RMS) error between the measured and the estimated values for the training and the testing. Fig. 4 shows the mean squared error values for different number of neurons. According to this figure, the RMS error for testing is 0.008. As it is obvious from Fig. 4, after 30 neurons, increasing number of the neurons does not offer any visible improvement in error values. It means that 30 is the optimal number for neuron size.

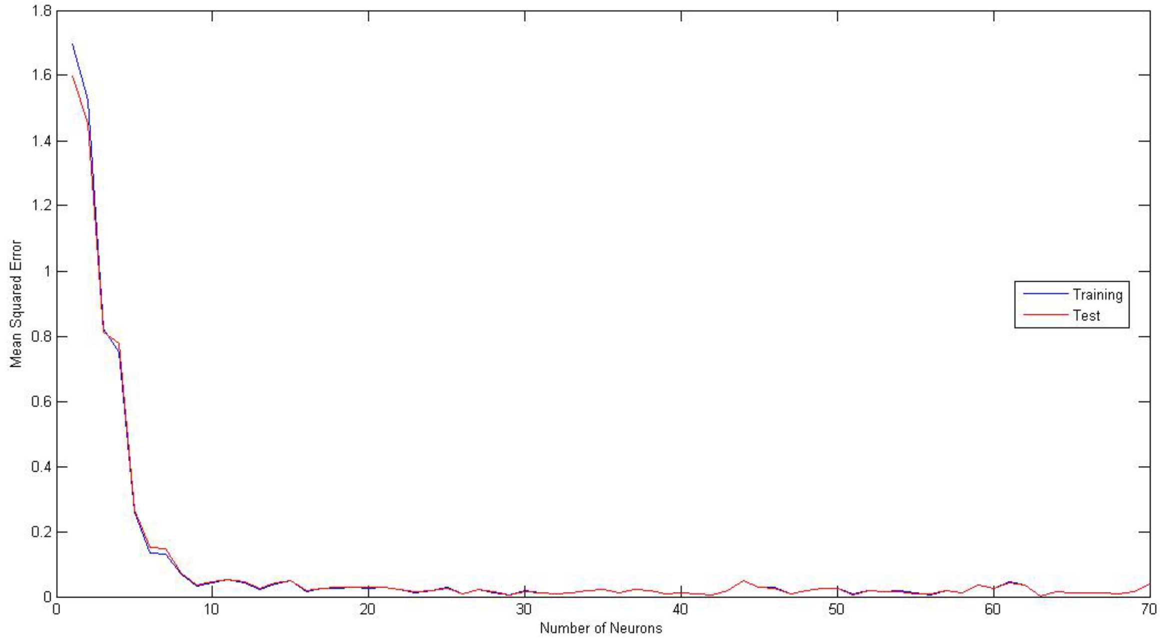

Fig.4: The Mean squared error values for different Neuron numbers

The effect of the number of hidden layers is also investigated. There are two extreme cases for the number of hidden layers: when there are too many parameters in analyzing, and when there are too few parameters. In similar studies, Ates [19] and Al-Faruk et al [20] used MLP with two hidden layers for prediction of some mechanical properties of the GMA welding. For study on the effect of the number of hidden layers, the percentage error values for one, two and three hidden layers is obtained and in contrast with the results by Al-Faruk et al [20], it found that when using one hidden layer the minimum error can be achieved. It is not surprising, because according to the theory of neural network, increasing the number of layers increases the generalization of the model while reduces the specialization and then the model will be able to predict more changes in values of the input parameters. However, increasing the number of layers causes increscent in error values. So, it should be done a compromise between error value and prediction capabilities of the model. Since the aim is providing a feedback for an automated GMA welding, and too much changes in input parameters during the welding is not expected, then the one layer MLP with low error value is the best option for our analysis.

The model accuracy is also evaluated by test data that was unseen for the model. As it can be seen from Fig. 5 the result of predictions by the model is in good agreement with test data set. It means that the model can predict the MD factor based on input parameters and then can control the input parameters to keep MD values inside a specific range. It should be noted that if the input parameters result an out of range MD values; a defect in welding is expected and that location should be marked for further investigations.

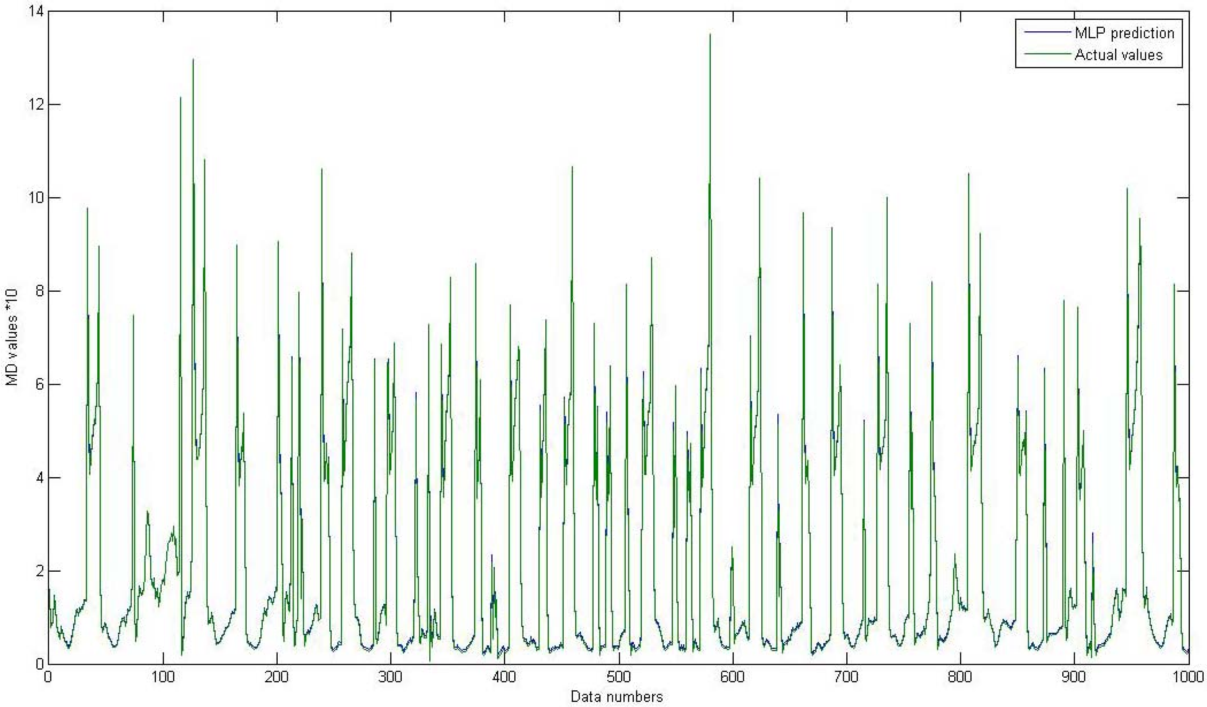

Fig. 5: The comparison between results from MLP and Test data

Additionally, some noises were added to the input data, to study the effect of potential noise error and then the robustness of the model. There are many sources for noise in GMA welding such as infects in power supply, cables and etc. The noise that is used in this study had variance of 0.03 and was produced randomly. Fig. 6 shows the noise for this study. As it is clear from Fig. 7, adding noise has not affected the model accuracy considerably and indicate that MLP model has a good robustness; the characteristic that is not assured in models such as regression analysis.

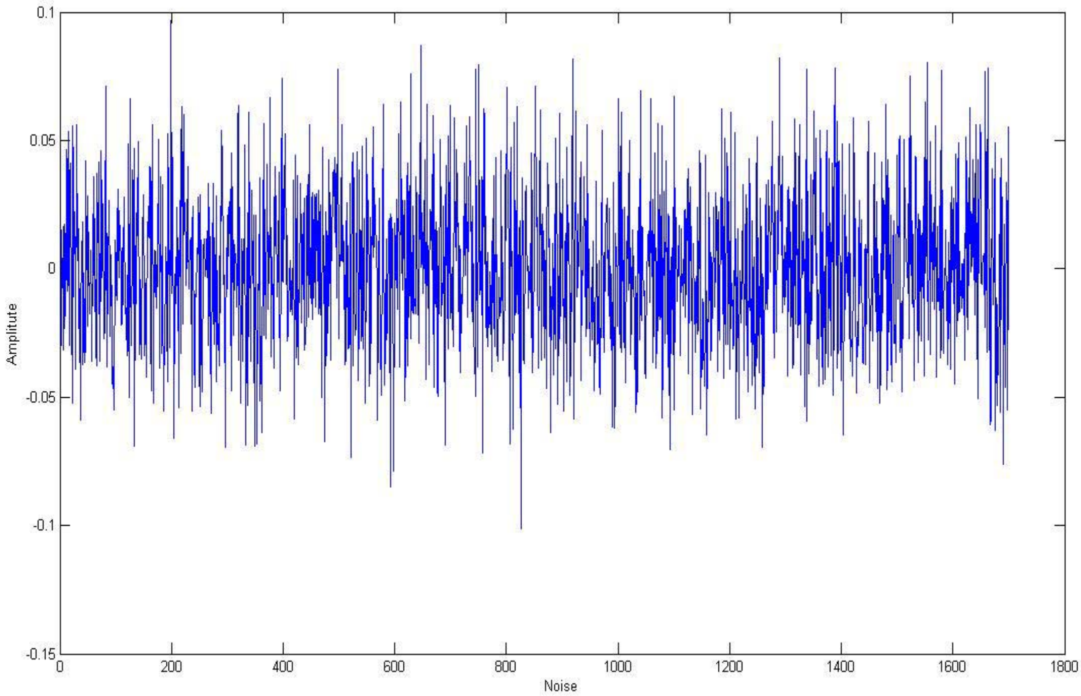

Fig. 6: The noise that is used in this work to study the robustness of the model

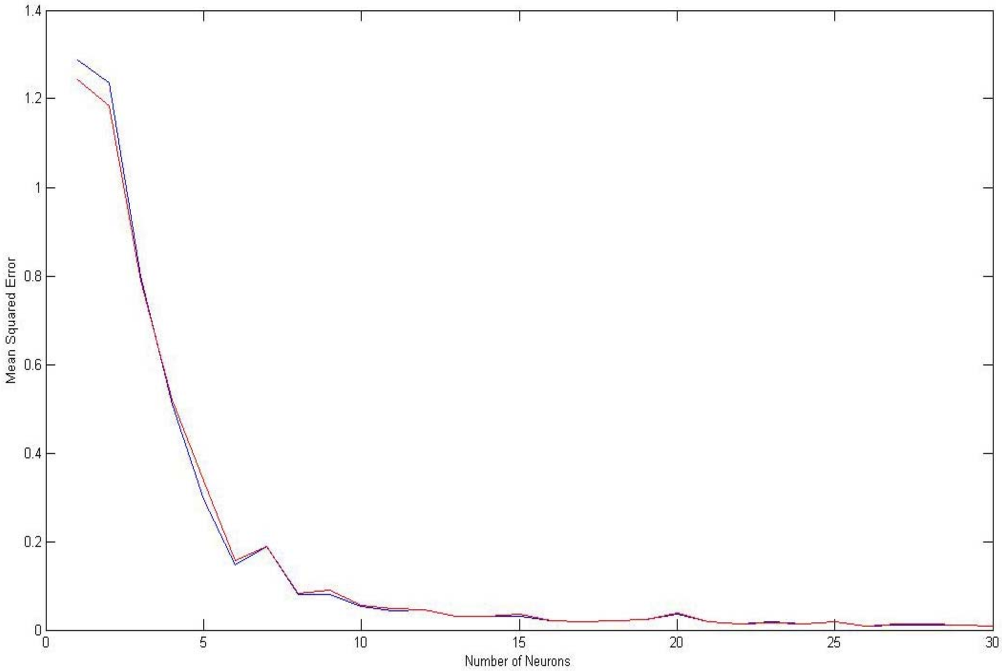

Fig. 7: The effect of Noise on error values

7. Conclusion

In this work the quality of GMA welding is evaluated by multi-layer perceptron (MLP) for using in online quality control of automated GMA system. In most of previous studies the pool geometry was considered as welding quality characteristic and therefore it was necessary to measure the bead width or bead heights and feed them into the prediction algorithm. However, recently it has been found that Mahalanobis Distance (MD) can be used effectively as a quality factor in GMA welding process. When MD is used as a characteristic parameter of welding, the quality can be checked by introduction of a sample which is easier than conventional methods. In this study, the Levenberg–Marquardt algorithm learning is used in MLP network in order to predict the MD based on input voltage and arc current. The results show good agreement when comparing test data set. Also, the effect of number of layers is studied and the results show that increasing in number of layers does not reduce the error values, and one layer MLP is the best choice for this kind of problem configuration. The robustness of the system was evaluated by adding random noise into input parameters and was found that the model has a good robustness against possible noises. Comparison between the error values of MLP model of this study with the similar error values published in literature shows that the model of this work has the lowest error value. All indicate that this network configuration can efficiently be used in prediction of MD and then the welding quality. It suggested using this procedure to investigate the quality and feedback parameters of welding in different positions (flat, horizontal, vertical down, vertical up, etc) and for different applications.

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